Article Type: Letters

The extent and predictability of the biodiversity-carbon correlation

Statement of authorship:

MDM and OV designed the study; MDM performed the research; all authors discussed the results and contributed to the writing.

Data accessibility statement

All the data used in this study derive from published sources, cited in the Methods section.

Authors

Di Marco, Moreno^{1,2}, James E.M. Watson^{2,3}, David J. Currie⁴, Hugh P. Possingham^{2,5}, Oscar Venter⁶

¹ CSIRO Land & Water, EcoSciences Precinct, 41 Boggo Road, Dutton Park Qld 4102, Australia

² Centre for Biodiversity and Conservation Science, The University of Queensland, 4072 Brisbane, Queensland, Australia.

³ Global Conservation Program, Wildlife Conservation Society, 2300 Southern Boulevard, Bronx, New York 10460, USA

⁴ Biology Department, University of Ottawa, 30 Marie Curie Priv. Ottawa, K1N 6N5 Ontario Canada

⁵ The Nature Conservancy, 4245 North Fairfax Drive, Suite 100 Arlington, VA 22203-1606, USA

⁶ Natural Resource and Environmental Studies Institute, University of Northern British Columbia, 3333 University Way, Prince George, V2N 4Z9, Canada.

Running title

This is the author manuscript accepted for publication and has undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process, which may lead to differences between this version and the [Version of Record](#). Please cite this article as [doi: 10.1111/ele.12903](https://doi.org/10.1111/ele.12903)

Predicting biodiversity-carbon correlation

Keywords

carbon density; conservation goals; macroecology; REDD+; scale; SDG; species richness.

Type of article

Letter

Word count

145 words in the Abstract; 5,076 words in the Main text; 80 References; 6 Figures.

Correspondence

Moreno Di Marco, EcoSciences Precinct, 41 Boggo Road, Dutton Park Qld 4102, Australia.

E: moreno.dimarco@gmail.com T: +61 7 3833 5940

Abstract

Protecting biomass carbon stocks to mitigate climate change has direct implications for biodiversity conservation. Yet, evidence that a positive association exists between carbon density and species richness is contrasting. Here we test how this association varies i) across spatial extents, and ii) as a function of how strongly carbon and species richness depend on environmental variables. We found the correlation weakens when moving from larger extents, e.g. realms, to narrower extents, e.g. ecoregions. For ecoregions, a positive correlation emerges when both species richness and carbon density vary as functions of the same environmental variables (climate, soil, elevation). In 20% of tropical ecoregions there are opportunities to pursue carbon conservation with direct biodiversity co-benefits, while other ecoregions require careful planning for both species and carbon to avoid potentially perverse outcomes. The broad assumption of a linear relationship between carbon and biodiversity can lead to undesired outcomes.

Introduction

The two greatest threats to life on Earth are anthropogenic climate change (Thomas *et al.* 2004; Scheffers *et al.* 2016) and land use change (Newbold *et al.* 2016; Venter *et al.* 2016), with ecological impacts spanning all scales of biological organisation, from genes to ecosystems (Scheffers *et al.* 2016). The interaction between these two threats and the management actions taken to ameliorate them is of primary conservation relevance, with rapid climate change expected to amplify the effect of land use change (Mantyka-Pringle *et al.* 2015; Visconti *et al.* 2016).

The establishment of protected areas in biologically diverse locations is the main strategy to minimize the impacts on biodiversity from land use change (Watson *et al.* 2014), while action to mitigate climate change focuses on the protection and restoration of high vegetative carbon stocks (Venter & Koh 2012). Protection of natural habitats that reduces land clearing can serve both the purpose of preserving carbon stocks and protecting ecosystems. This means that different environmental policy goals, such as climate change mitigation and biodiversity conservation, can be achieved simultaneously with the same investment (Di Marco *et al.* 2016). A much-debated example of carbon conservation schemes is the UN mechanism for Reducing Emissions from Deforestation and forest Degradation (REDD+), which is primarily aimed at reducing global greenhouse gas emissions but can have also direct implications for biodiversity conservation (Venter *et al.* 2009a; Thomas *et al.*

2013). Understanding the relationship between carbon and biodiversity, and their potential conservation synergies, is fundamental for achieving both goals under this scheme.

A dual benefit is expected when financial resources are mobilised towards the conservation of areas with high carbon and biodiversity content that are at high risk of deforestation (Venter *et al.* 2009a), but preventive carbon credits can also benefit highly forested countries with low current deforestation rates (Da Fonseca *et al.* 2007). However, reducing deforestation in a carbon-rich area might also have negative implications for biodiversity, if the deforestation is reallocated to areas with lower carbon but higher biodiversity content (a phenomenon known as ‘leakage’; Gan & Mccarl 2007). At the same time, actions to prevent climate change have also raised concerns for biodiversity conservation as they can result in the modification of natural habitats, such as biofuel plantations replacing natural forests (Danielsen *et al.* 2009) or afforestation of areas rich in non-forest biodiversity (Brockerhoff *et al.* 2008; Lindenmayer *et al.* 2012). Such perverse outcomes at most likely when biodiversity and carbon density are weakly or even negatively correlated (Paoli *et al.* 2010).

To date, the evidence of a positive correlation between biodiversity and carbon density is mixed, with different studies reporting contrasting findings. Some authors have found a positive correlation between the global variation of terrestrial carbon and the variation of vertebrate species richness (Strassburg *et al.* 2010; Buchanan *et al.* 2011; Siikamäki & Newbold 2012). Others have found a weak or moderate correlation in national and sub-national analyses, for example using threatened mammals in Borneo (Venter *et al.* 2009b), terrestrial vertebrates in Colombia (Armenteras *et al.* 2015) and Costa-Rica (Locatelli *et al.* 2013), and tree species in central Africa (Day *et al.* 2013). In contrast, several analyses have revealed limited, or even negative, correspondence between species richness and carbon in UK (Anderson *et al.* 2009), Indonesia (Paoli *et al.* 2010; Murray *et al.* 2015), and Colombia at a sub-national extents (Armenteras *et al.* 2015). This was also observed when analysing fine grain (plot-level) carbon data in tropical forests around the globe, with no correlation found with vertebrate (Beaudrot *et al.* 2016) or plant (Sullivan *et al.* 2016) biodiversity.

Contrasting evidence on the correlation between biodiversity and carbon may reflect the diversity of studies in terms of geographic location (including the natural variation of the study areas), taxonomic groups analysed, and carbon measured (e.g. above- and/or below-ground). At a global extent, wet tropical areas tend to be richer in biodiversity than temperate

areas (Gaston 2000), and also contain high stored carbon (Ruesch & Gibbs 2008). However, at more local extents the potential for co-benefits can be much more limited, especially in silvicultural and agroforestry landscapes in the tropics, where altering the composition of natural ecosystems can result in relatively high carbon sequestration with a substantial reduction of species diversity (Putz & Redford 2009; Kessler *et al.* 2012; Lindenmayer *et al.* 2012).

Overall, a pattern emerges from the literature, with global-extent analyses being more likely to reveal a positive correlation (Strassburg *et al.* 2010) than regional- or local-extent analyses (Buchanan *et al.* 2011; Armenteras *et al.* 2015). This may be related to the fact that the spatial variation in the environmental drivers of biodiversity and carbon, such as climate, is higher at larger spatial extents (Field *et al.* 2009). In fact, at the global extent, spatial variation in species richness (Kreft & Jetz 2007; Belmaker & Jetz 2015), primary productivity (Rosenzweig 1968; Cramer *et al.* 1999), and soil carbon (Cao & Woodward 1998), are all strongly correlated with climate. At regional or local extents the role of other variables in driving these ecosystem properties can become predominant, species richness for example may depend upon factors like topographic heterogeneity (Kerr & Packer 1997), soil properties (Stevens *et al.* 2004), or Quaternary glacial history (Normand *et al.* 2011). Regional carbon density may also deviate from that expected due to climate regimes, for example when wildland fire disturbance is prevalent (Midgley *et al.* 2010). At narrower extents, it is also expected that both carbon density and species richness show less variation than at larger extents, and this in turn influences their correlation. The choice of an appropriate spatial extent for analysing this relationship is thus of particular relevance to making management and policy decisions (Blackburn & Gaston 2002; Rahbek 2005), with the potential for contrasting findings to emerge at different extents (Armenteras *et al.* 2015).

Here we analyse how the correlation between species richness, one of the most investigated measures of biodiversity (Field *et al.* 2009), and carbon density varies from global to local extents, and what influences the correlation locally. We adopt the biogeographical subdivision of the world produced by Olson and colleagues (2001) to measure the correlation between carbon density and species richness among ecoregions, biomes, realms, and the globe. Since we were specifically interested in the role of spatial extent (i.e. the size of the study region; (Blackburn & Gaston 2002)), we employed a fixed grain size in our analysis, after performing a sensitivity test (see also (Belmaker & Jetz 2011) for a comprehensive analysis of grain size). We then use ecoregions, the smallest extent in

our analysis, to test the predictability of the biodiversity-carbon correlation. We hypothesize that the correlation between biodiversity and carbon depends on (i) the spatial extent considered, decreasing in strength when moving from a global to an ecoregional extent, and (ii) the predictability of both species richness and carbon density from a suite of environmental variables.

Methods

Carbon and biodiversity data

We represented carbon density (Fig. 1a) using a 1km map of the above-ground vegetation biomass in tropical and subtropical regions worldwide (Avitabile *et al.* 2016). This is an up-to-date pantropical map that combines two comprehensive recent estimates of carbon density (Saatchi *et al.* 2011; Baccini *et al.* 2012). The two estimates of carbon density were built using a similar methodology – based on a combination of Modis and LiDAR satellite images – but adopted different calibration data, resulting in some significant differences. The combined pantropical map resolves these inconsistencies using a fusion model calibrated on a reference carbon dataset. We tested the sensitivity of our results to the carbon measure adopted, by using a different 1km map (Fig. S1) representing the above- and below-ground vegetation biomass for tropical and temperate areas of the entire globe (Ruesch & Gibbs 2008). This map, already used in previous studies (Strassburg *et al.* 2010), applied the International Panel on Climate Change Tier-1 method (IPCC 2006) for estimating carbon stocks of vegetation types in different ecoregions. Both carbon maps were resampled to a resolution of 10 km using average pixel values (see below for a description of our grain size choice).

We used species richness as our biodiversity metric for each grid cell. We defined species richness maps (Fig. 1b) from the geographic ranges of terrestrial amphibians ($n = 6,407$), birds ($n=10,424$), and mammals ($n=5,312$) (Birdlife International & NatureServe 2015; IUCN 2016). We rasterised species ranges at a resolution of 10 km, which represents a compromise between computational tractability and data accuracy (Di Marco *et al.* 2017). This resolution is in line with that adopted in previous national-extent analyses using similar data (Armenteras *et al.* 2015), but is finer than the resolution previously adopted for global-extent analyses (Strassburg *et al.* 2010). Employing a 10 km resolution, when measuring

species richness from IUCN range maps, can lead to overestimation of richness due to commission errors in the maps, i.e. areas included as part of the geographic range of a species even if the species is actually absent (Hurlbert & Jetz 2007; Jetz *et al.* 2008). Employing coarser analytical resolutions can reduce the effect of commission errors, but also reduces statistical power by reducing the number of available grid cells. Coarsening the resolution also leads to more area having to be selected in spatial prioritisation analyses, making the selection less cost-efficient without significantly altering the overall results (Montesino Pouzols *et al.* 2014; Di Marco *et al.* 2017). To measure the sensitivity of our results to the spatial resolution adopted, we repeated our test of the first hypothesis after changing the resolution from 10 km to 100 km. In this case we used the global carbon map (Ruesch & Gibbs 2008), as opposed to the pantropical one, to include as many ecoregions and biomes as possible (using a cut-off rule of at least 10 grid cells each).

Testing hypothesis 1: the correlation between species richness and carbon density deteriorates when spatial extent decreases

We used the hierarchical subdivisions of the world produced by Olson and colleagues (2001) – globe, realms, biomes within realms, and ecoregions – to test the correlation between species richness and carbon density at different spatial extents. We estimated the correlation between carbon and species richness across all grid cells in each analytical region, using the Spearman's rank correlation coefficient (r_s ; Strassburg *et al.* 2010; Armenteras *et al.* 2015). We first calculated the correlation value at a global extent, and then calculated the mean correlation value, and 95% credible interval, at each geographic extent (realms, biomes, and ecoregions). We tested whether the correlation values observed at a given biogeographical extent were significantly lower than the values observed at broader extents (one sided t-test). We calculated these correlations both for total species richness, aggregated across the three vertebrate classes, and for the species richness in individual classes.

We verified whether our estimates of the species-carbon correlation were influenced by the presence of human-modified environments, where the natural distribution of both species and carbon is expected to be substantially altered. To do this, we repeated our analyses after excluding areas of high human pressure, as identified by values of Human Footprint of ≥ 4 (in a 0-50 range; Venter *et al.* 2016; Watson *et al.* 2016). We also verified whether our results were influenced by the coarse distribution data used in our analyses,

repeating the analyses for mammals using habitat suitability models available from Rondinini *et al.* (2011). These models derive from a systematic classification of the species' habitat preferences reported in the IUCN Red List, and represent refined species distribution that exclude areas of unsuitable habitat from each species' range. Using these models we were also able to identify ecoregions where the use of IUCN species ranges lead to an overestimation of species richness (Rondinini *et al.* 2011), thereby generating uncertainty in the estimation of species-carbon correlation. Finally, we repeated our analysis using only threatened species, as classified in the IUCN Red List, since these are the species of highest immediate conservation concern.

We excluded from the analyses ecoregions with an area smaller than 5,000 km², which have low statistical power (Watson *et al.* 2016). We also excluded ecoregions in which carbon data were available for less than 50% of their area.

Testing hypothesis 2: the correlation between species richness and carbon density depends on how strongly each is related to environmental variables

Modelling carbon density and species richness

We hypothesized that the strength of the species richness-carbon density correlation is a function of how strongly each is related to environmental variables. We used individual ecoregions as our analytical units, because these represented the finest biogeographical extent in our hierarchical analyses. We ran two separate models within each ecoregion, one relating carbon density to environmental variables, and one relating species richness to those variables. We retained all areas in this analysis, but tested the role of disturbance factors in altering the species-carbon correlation in ecoregions (see next section). The main focus of our work is to identify general patterns and drivers of the species richness-carbon density correlation, rather than testing several alternative hypotheses behind the distribution of the two variables. We thus employed relatively simple, and consistent, model structures to predict both species richness and carbon density as functions of climate, soil characteristics, and altitude.

Following previous approaches (Iwamura *et al.* 2013), we selected six bioclimatic variables from the WorldClim dataset (Hijmans *et al.* 2005) to represent ecoregions' climatic profiles: annual mean temperature, mean diurnal temperature range, temperature annual

range, annual precipitation, precipitation seasonality, precipitation of the driest quarter. We also included potential evapotranspiration (Trabucco & Zomer 2009). In order to prevent potential collinearity issues among the bioclimatic variables, we ran a principal component analysis on the variables and extracted the two principal axes (representing 79% of the variance). We also selected seven descriptors of soil characteristics (Global Soil Data Task Group 2000): bulk density, field capacity, profile available water capacity, thermal capacity, total nitrogen density, wilting point. Similar to climate data, we ran a principal component analysis on the soil variables (Sullivan *et al.* 2016) and used the two principal axes as predictors (representing 77% of the variance). In addition to climatic and soil variables, we also included elevation above sea level (USGS 2006) as an environmental predictor.

In order to account for spatial autocorrelation in model residuals, we used spatial simultaneous autoregressive error models (SAR; Kissling & Carl 2007). For each ecoregion we selected the neighbourhood distance resulting in the lowest AIC value for the SAR models, testing carbon models and species richness models separately. The tested distances (15, 50, 100 km) span the magnitude of values found to be significant in other similar studies (Tognelli & Kelt 2004; Kissling & Carl 2008). We measured the variance explained by the environmental variables in each SAR model as the square of the correlation between observed response (either carbon or species richness) and predicted response. Since we were interested in the relative contribution of environmental characteristics, we only considered the proportion of variance explained by the models' variables and excluded the portion of variance explained by the spatial autocorrelation (Faurby & Svenning 2015; Santini *et al.* 2017). The explained variance measured that way is typically lower than the variance explained by the full model, and we report both values for comparison.

Determining the drivers of the correlation between species richness and carbon density

For each ecoregion, we coupled the outcome of environmental models (their R^2 values excluding the contribution of spatial autocorrelation) with the following variables: biome and realm where the ecoregion is found, area of the ecoregion, fractal dimension of the ecoregion (e.g. to account for different shapes between coastal vs inland ecoregions), standard deviation of carbon density and species richness within the ecoregion. Accounting for standard deviation is necessary to control for the effect that natural variation in species richness and carbon have in determining high or low correlation between the two. We also accounted for

three disturbance factors in our models. The first factor is the proportion of the ecoregion surface where Human Footprint is ≥ 4 (on a 0-50 range), which is considered a value of significant human pressure (Venter *et al.* 2016; Watson *et al.* 2016). The second factor is the average year in which the first human alteration of land use in the ecoregion was registered, as derived from the KK10 model of historical land-use intensity, spanning 6,000 BC to 2,000 AD (Ellis *et al.*, 2013). The third factor is wildland fire, which plays a key role in shaping carbon density and biodiversity in some ecosystem (Midgley *et al.* 2010); we measured fire extent as the average area burnt per year (over the period 1996-2016) using the GFED4 dataset (Giglio *et al.* 2013).

We ran a random forest regression model (Breiman 2001) to identify the most important predictors of the spatial variation in the species richness-carbon correlation among ecoregions, as a function of the above-listed variables (R^2 of environmental models, biome and realm, size and fractal dimension of the ecoregion, SD of species richness and carbon, disturbance). We then used partial dependence plots to represent the marginal effect of each numerical variable on the correlation between species richness and carbon. We also repeated the analyses within individual realms to represent the relative contribution of fire regimes in different systems.

All analyses were run using freely available software. Spatial data preparation was done in GrassGIS (GRASS Development Team 2016). Statistical analyses were done in R (R Core Team 2015), using the packages ‘spdep’ (Bivand & Piras 2015), ‘randomForest’ (Liaw & Wiener 2002), and ‘party’ (Strobl *et al.* 2009).

Results

Testing hypothesis 1: the correlation between species richness and carbon density deteriorates when spatial extent decreases

When using the pan-tropical above-ground carbon map, we identified 437 ecoregions with a total area size of at least 5,000 km² and >50% of their area covered by carbon data. We found a moderate positive correlation between vertebrate species richness and carbon density at the global extent ($r_s = 0.48$), and a slightly higher mean correlation at the extent of realms (mean $r_s = 0.55$, sd = 0.26). The correlation was much weaker within biomes (mean $r_s = 0.31$, sd = 0.27) and even more so within ecoregions (mean $r_s = 0.22$, sd = 0.30) (Fig. 2a). With the

exception of `realms vs the globe`, the correlation values observed at a given biogeographical extent were always lower than those observed at larger extents with a significance level of 0.05 or below (Table S1). This exception is removed when excluding areas with high human pressure from the analysis (Table S2), and when looking at the global distribution of above- and below-ground carbon (Table S3).

We plotted the values of the correlation in each tropical and sub-tropical ecoregion to show areas where investments in carbon conservation are most likely to deliver biodiversity co-benefits (Fig. 3). The map shows high variation in correlation values among ecoregions, from very negative ($r_s = -0.64$) to very positive ($r_s = 0.84$). We observed high correlation values in Madagascar, continental Southeast Asia, northern and eastern Australia, and part of South America.

Similar to the all-species analysis, the correlation between species richness and carbon become on average weaker from global to narrower extents when looking at individual vertebrate classes (Fig. 2b-d). This pattern was qualitatively confirmed, and was even stronger, when repeating the analyses only on areas not affected by high levels of human pressure (Fig. S2). Our sensitivity testing on resolution also showed consistent results when employing a 100 km grid instead of 10 km (Fig. S3), but in this case half of the ecoregions were removed from analyses due to having fewer than 10 grid cells. When using habitat suitability models to represent the distribution of terrestrial mammal species, we obtained almost identical correlations as when we used IUCN range maps (Fig. S4). We were also able to identify areas where the use of IUCN maps could lead to potential uncertainty in our spatial results (Fig S5). We found most ecoregions (>80%) had a very similar level of species richness when using habitat suitability models or IUCN ranges (average similarity of 90% or more) but there were exceptions, especially in central Asia, where the species richness measured from habitat models represented only 60% of the richness measured from IUCN ranges. In those regions, the interpretation of our spatial results requires caution. Finally, when only considering threatened species the correlation with carbon density was generally lower than when all species were considered (Fig. S6).

These results overall provide support for our first hypothesis that the biodiversity-carbon correlation is on average higher at broad spatial extent and lower at smaller extents, and demonstrate the finding is robust to data uncertainty and the analytical settings.

Testing hypothesis 2: the correlation between species richness and carbon density depends on how strongly each is related to environmental variables

Modelling carbon density and species richness

We tested the ability of environmental variables to account for the spatial variation of both carbon density and species richness within each ecoregion. The performance of the two sets of SAR models was quite variable among ecoregions, with a strong effect of spatial autocorrelation, especially for species richness (Fig. 4). The overall performance of species richness models (mean $R^2 = 0.92$, sd $R^2 = 0.13$) was higher than carbon models (mean $R^2 = 0.72$, sd $R^2 = 0.15$). However, this was not the case when only considering the contribution of environmental variables to the models (excluding the spatial autocorrelation component), with both sets of models having similar performances (species richness models: mean $R^2 = 0.29$, sd $R^2 = 0.25$; carbon models: mean $R^2 = 0.27$, sd $R^2 = 0.21$).

Determining the drivers of the correlation between species richness and carbon density

The most important predictors of the correlation between species richness and carbon density was the predictability of carbon from environmental variables (Fig. 5). Other important predictors were the standard deviation of species richness, the predictability of species richness from environmental variables, and the average year of first human land use in the ecoregion. We represented the marginal effect of each predictor on the species-carbon correlation using partial dependence plots (Fig. S7), and found that higher correlation values were observed with higher performance of the environmental prediction models, higher SD of carbon and species richness, and higher levels of disturbance (human impact, and fire extent). We represented the relative contribution of fire regimes in different realms, and found the species-carbon correlation in the Afrotropics and the Neotropics was negatively associated with high fire extents, while Australasia had a positive association and the Indomalay region had high correlation observed at both low and high levels of fire extents (Fig. S8). Finally, a bivariate plot showed that the species-carbon correlation value was particularly high in those ecoregions where both carbon and species richness had strong relationships with environmental variables (Fig. 6).

These results are overall consistent with our second hypothesis that the correlation between species richness and carbon density is higher in those ecoregions where both

variables can be successfully predicted from environmental conditions (climate, soil, altitude).

Discussion

Years of debate on whether it is possible simultaneously to conserve biodiversity and stored carbon (Venter *et al.* 2009a; Gardner *et al.* 2012; Thomas *et al.* 2013; Armenteras *et al.* 2015) have failed to give an unambiguous answer. Yet this question has significant practical implications for carbon policies and site-based conservation actions. Here we provide a comprehensive multi-extent analysis of where a positive correlation is most likely to occur, and discuss two general findings. First, we found the correlation is lower when moving from a larger to a narrower extent (e.g. global/realms to biomes/ecoregions). This result was robust to variations in the group of species analysed, the use of refined species distributions, the removal of human modified areas, and the analytical resolution employed, demonstrating the general validity of the finding. This is consistent with previous findings that the association between species richness and environmental variables is weaker in studies performed over smaller scales, i.e. small extents and small grain sizes (Field *et al.* 2009; Belmaker & Jetz 2011). Second, we found a positive correlation is more likely in geographic domains in which both species richness and carbon density vary as predictable functions of environment characteristics. We showed that this is not simply related to the natural variability in species richness and carbon density. When controlling for standard deviation in carbon and species richness, and for disturbance factors operating in each ecoregion, we still found the species-carbon correlation was positively associated with the predictability of the two variables from environmental characteristics. In fact, the ability of environmental models to predict carbon density was the most important driver of the species-carbon correlation.

We found high heterogeneity in the species richness-carbon correlation among ecoregions, but showed that there are still opportunities to pursue local carbon conservation with high biodiversity co-benefits. In tropical and subtropical areas, 20% of ecoregions have a high correlation value ($r_s \geq 0.5$), while 34% have very low or even negative values ($r_s \leq 0.1$). This means that it is important to be strategic in planning carbon and biodiversity investments. Efforts to protect carbon will likely deliver direct and important biodiversity benefits in ecoregions with high positive correlation values. However this focus is not a

panacea, and a mixed strategy will be necessary elsewhere, where actions directly aimed at protecting biodiversity need to be complemented with carbon schemes to obtain a double benefit (Venter *et al.* 2009a; Thomas *et al.* 2013). This is especially relevant in areas that are rich in biodiversity, have a low or negative carbon-biodiversity correlation, and are at potential risk of habitat loss displacement (e.g. deforestation being stopped in one place but reallocated in another). In these areas it is fundamental to couple the protection of carbon-dense sites with the protection of important sites for biodiversity, to avoid potential detrimental effects of carbon schemes on biodiversity. Biodiversity conservation, including the global reduction of extinction rates, relies largely on local actions (Boyd *et al.* 2008) and many sites are irreplaceable due to the unique biodiversity they host. On the contrary, there are typically several options to achieve climate change mitigation through carbon sequestration. Hence, there may be a case for giving priority to biodiversity conservation at local extents where trade-offs with carbon conservation emerge, particularly in ecoregions in which the absolute amount of carbon storage is low.

Many ecoregions with negative correlation between species richness and carbon values hosts dry savannah and grassland environments with low variation in carbon content, such as the Somali Acacia-Commiphora bushlands and thickets, the Western Australia Mulga shrublands, and the Patagonian Steppe. These are fire- and browse-driven systems where diversity is related to lower carbon density, where species diversity might not be necessarily associated with the presence of trees, which explains the lack of a positive association with carbon storage. However, a recent study (Bastin *et al.* 2017), using visual interpretation of very-high resolution satellite imagery, suggests that tree density in dryland biomes might be underestimated when using medium-resolution satellite imagery, and this might also affect the measure of species-carbon correlation in these environments. Other regions where negative correlations were observed are characterised by low variation in species richness, which was either consistently high throughout the ecoregion, such as the Purus-Madeira moist forest in the Amazon, or relatively low throughout, such as in some deserts. We also observed negative correlation in ecoregions which were almost entirely converted to anthropogenic uses, such as the Southern Korean Evergreen Forests and the Guizhou Plateau broadleaf and mixed forests in China. However ecoregions with a long history of human land use were characterised by relatively higher carbon-richness correlation. This is likely related to the alteration of natural habitat, which reduces the space available for the manifestation of key ecosystem properties (such as carbon storage and species diversity). This also implies

that the protection of remaining natural habitats in ecoregions with a long history of human land use is likely to serve both biodiversity and carbon conservation purposes.

Carbon density is known to be affected by fire regimes associated with seasonal climates in the subtropics (Midgley *et al.* 2010), while high biodiversity can exist in those areas due to specific fire adaptations (Bond & Parr 2010). When considering all ecoregions, we found relatively little influence of fire extent on the species-carbon correlation (Fig S7). However, when separating the effect for individual realms (Fig S8), we found that fire extent in the Neotropics and particularly in the Afrotropics were negatively associated with the species-carbon correlation. This highlights the importance of considering the trade-offs between carbon sequestration policies and conservation of biodiversity in fire-driven systems (Midgley & Bond 2015).

The correlation between species richness and carbon was weaker if only considering species threatened with extinction, especially when looking at broader spatial extents (biomes, realms, or the globe). This was already discussed by Strassburg *et al.* (2010), and is not surprising: while the global variation in both carbon storage and species richness is primarily climate-dependent, the richness in threatened species is more influenced by anthropogenic pressures. However, there are still ecoregions (18% of all pantropical ecoregions) in which the correlation of threatened species richness with carbon value is high ($r_s \geq 0.5$). These ecoregions represent important opportunities for using carbon conservation schemes to conserve areas with high concentration of threatened species, contributing to two of the most important challenges for global biodiversity conservation.

Mitigating climate change and halting biodiversity loss represent key objectives for achieving sustainable development (United Nations General Assembly 2015). Evidence for the existence of a positive correlation between biodiversity and carbon is mixed, and many have argued that action to mitigating climate change might have a negative impact on biodiversity. Thereby, acting on the presumption of a linear positive relationship between carbon and biodiversity can lead to perverse outcomes in the many areas where this assumption does not hold. Carbon policies applied at large spatial extents (i.e. encompassing multiple biomes within a realm, or the globe) are likely to have positive effects on species conservation. Management interventions planned within individual ecoregions can lead to trade-offs, and requires considering the environmental factors that drive the correlation between carbon and species. Areas with high species-carbon correlation represent immediate

opportunity for achieving both objectives. Areas with low, or even negative, correlation should be approached with caution in carbon conservation schemes. In these regions, it is essential that biodiversity monitoring and conservation measures are put in place to avoid potentially perverse outcomes, such as natural habitat alteration or displacement of habitat loss into high biodiversity areas.

Acknowledgements

We thank four anonymous reviewers for their insightful comments that improved our paper. We thank Carlo Rondinini and the Global Mammal Assessment lab in Sapienza University of Rome for providing mammal species distribution models used in the sensitivity analyses. MDM was supported by the ARC Centre of Excellence for Environmental Decision.

References

- Anderson, B.J., Armsworth, P.R., Eigenbrod, F., Thomas, C.D., Gillings, S., Heinemeyer, A., *et al.* (2009). Spatial covariance between biodiversity and other ecosystem service priorities. *J. Appl. Ecol.*, 46, 888–896
- Armenteras, D., Rodríguez, N. & Retana, J. (2015). National and regional relationships of carbon storage and tropical biodiversity. *Biol. Conserv.*, 192, 378–386
- Avitabile, V., Herold, M., Heuvelink, G.B.M., Lewis, S.L., Phillips, O.L., Asner, G.P., *et al.* (2016). An integrated pan-tropical biomass map using multiple reference datasets. *Glob. Chang. Biol.*, 22, 1406–1420.
- Baccini, a., Goetz, S.J., Walker, W.S., Laporte, N.T., Sun, M., Sulla-Menashe, D., *et al.* (2012). Estimated carbon dioxide emissions from tropical deforestation improved by carbon-
- Bastin, J.-F., Berrahmouni, N., Grainger, A., Maniatis, D., Mollicone, D., Moore, R., *et al.* (2017). The extent of forest in dryland biomes. *Science*, 356, 635–638
- Beaudrot, L., Kroetz, K., Alvarez-Loayza, P., Amaral, I., Breuer, T., Fletcher, C., *et al.* (2016). Limited carbon and biodiversity co- benefits for tropical forest mammals and birds. *Ecol. Appl.*, 26, 1098–1111
- Belmaker, J. & Jetz, W. (2011). Cross-scale variation in species richness-environment associations. *Glob. Ecol. Biogeogr.*, 20, 464–474

501 Belmaker, J. & Jetz, W. (2015). Relative roles of ecological and energetic constraints,
 502 diversification rates and region history on global species richness gradients. *Ecol.*
 503 *Lett.*, 18, 563–571
 504 BirdLife International & NatureServe. (2015). *Bird species distribution maps of the world*
 505 *version 5.0*. BirdLife International and NatureServe, Cambridge, UK and Arlington,
 506 USA.
 507 Bivand, R. & Piras, G. (2015). Comparing Implementations of Estimation Methods for
 508 Spatial Econometrics. *J. Stat. Softw.*, 63, 1–36
 509 Blackburn, T.M. & Gaston, K.J. (2002). Scale in macroecology. *Glob. Ecol. Biogeog.*, 185–
 510 189
 511 Boyd, C., Brooks, T.M., Butchart, S.H.M., Edgar, G.J., Da Fonseca, G. a B., Hawkins, F., *et*
 512 *al.* (2008). Spatial scale and the conservation of threatened species. *Conserv. Lett.*, 1,
 513 37–43
 514 Breiman, L. (2001). *Random forests*. University. Berkeley, CA
 515 Brouckhoff, E.G., Jactel, H., Parrotta, J.A. , Quine, C.P. & Sayer, J. (2008). Plantation
 516 forests and biodiversity: Oxymoron or opportunity? *Biodivers. Conserv.*, 17, 925–951
 517 Buchanan, G.M., Donald, P.F. & Butchart, S.H.M. (2011). Identifying priority areas for
 518 conservation: a global assessment for forest-dependent birds. *PLoS One*, 6, e29080
 519 Cao, M. & Woodward, F. (1998). Net primary and ecosystem production and carbon stocks
 520 of terrestrial ecosystems and their responses to climate change. *Glob. Chang. Biol.*, 4,
 521 185–198
 522 Cramer, W., Kicklighter, D.W., Bondeau, a, Moore, B., Churkina, G., Nemry, B., *et al.*
 523 (1999). Comparing global models of terrestrial net primary productivity (NPP):
 524 overview and key results. *Glob. Chang. Biol.*, 5, 1–15
 525 Danielsen, F., Beukema, H., Burgess, N.D., Parish, F. , Brühl, C.A. , Donald, P.F. *et al.*
 526 (2009) Biofuel Plantations on Forested Lands: Double Jeopardy for Biodiversity and
 527 Climate. *Conserv. Biol.*, 23, 348–358
 528 Day, M., Baldauf, C., Rutishauser, E. & Sunderland, T.C.H. (2013). Relationships between
 529 tree species diversity and above-ground biomass in Central African rainforests:
 530 implications for REDD. *Environ. Conserv.*, 41, 64–72

531 Da Fonseca, G.A.B., Rodriguez, C.M., Midgley, G., Busch, J., Hannah, L. & Mittermeier,
532 R.A. (2007) No forest left behind. *PLoS Biol.*, 5, 1645–1646

533 Di Marco, M., Butchart, S.H.M., Visconti, P., Buchanan, G.M., Ficetola, G.F. & Rondinini,
534 C. (2016). Synergies and trade-offs in achieving global biodiversity targets. *Conserv.*
535 *Biol.*, 30, 189–195

536 Di Marco, M., Watson, J.E.M., Possingham, H.P. & Venter, O. (2017). Limitations and trade-
537 offs in the use of species distribution maps for protected area planning. *J. Appl. Ecol.*,
538 54, 402–411

539 Faurby, S. & Svenning, J.C. (2015). Historic and prehistoric human-driven extinctions have
540 reshaped global mammal diversity patterns. *Divers. Distrib.*, 21, 1155–1166

541 Field, R., Hawkins, B. A., Cornell, H. V., Currie, D.J., Diniz-Filho, J.A.F., Guégan, J.F., *et*
542 *al.* (2009). Spatial species-richness gradients across scales: A meta-analysis. *J.*
543 *Biogeogr.*, 36, 132–147

544 Gan, J. & Mearns, B.A. (2007). Measuring transnational leakage of forest conservation. *Ecol.*
545 *Econom.*, 64, 423–432

546 Gardner, T.A., Burgess, N.D., Aguilar-amuchastegui, N., Barlow, J., Berenguer, E.,
547 Clements, T., *et al.* (2012). A framework for integrating biodiversity concerns into
548 national REDD + programmes. *Biol. Conserv.*, 154, 61–71

549 Gaston, K.J. (2000). Global patterns in biodiversity. *Nature*, 405, 220–227

550 Giglio, L., Randerson, J.T. & Van Der Werf, G.R. (2013) Analysis of daily, monthly, and
551 annual burned area using the fourth-generation global fire emissions database
552 (GFED4). *J. Geophys. Res. Biogeosciences*, 118, 317–328

553 Global Soil Data Task Group. (2000). *Global Gridded Surfaces of Selected Soil*
554 *Characteristics (IGBP-DIS)*. Oak Ridge Natl. Lab. Oak Ridge, USA. Available at .
555 [Http://www.daac.ornl.gov](http://www.daac.ornl.gov). Last accessed: 01 Dec 2016

556 GRASS Development Team. (2016). Geographic Resources Analysis Support System
557 (GRASS) Software, Version 7.0. Open Source Geospatial Foundation.

558 Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G. & Jarvis, A. (2005). Very high
559 resolution interpolated climate surfaces for global land areas. *Int. J. Climatol.*, 25,
560 1965–1978

561 Hurlbert, A.H. & Jetz, W. (2007) Species richness, hotspots, and the scale dependence of
562 range maps in ecology and conservation. *PNAS*, 104, 13384–13389

563 IPCC (2006) *IPCC Guidelines for National Greenhouse Gas Inventories. Volume 4:*
564 *Agriculture, Forestry and Other Land Use.*

565 IUCN. (2016). *IUCN Red List of Threatened Species. Version 2016.1.* Available at:
566 www.iucnredlist.org.

567 Iwamura, T., Guisan, A., Wilson, K. a. & Possingham, H.P. (2013). How robust are global
568 conservation priorities to climate change? *Glob. Environ. Chang.*

569 Jenkins, C.N., Pimm, S.L. & Joppa, L.N. (2013). Global patterns of terrestrial vertebrate
570 diversity and conservation. *PNAS*, 110, E2602-10

571 Jetz, W., Sekercioglu, C.H. & Watson, J.E.M. (2008). Ecological Correlates and
572 Conservation Implications of Overestimating Species Geographic Ranges. *Conserv.*
573 *Biol.*, 22, 110–119

574 Kerr, J.T. & Packer, L. (1997). Habitat heterogeneity as a determinant of mammal species
575 richness in high-energy regions. *Nature*, 385, 252-254

576 Kessler, M., Hertel, D., Jungkunst, H.F., Kluge, J., Abrahamczyk, S., Bos, M., *et al.* (2012).
577 Can Joint Carbon and Biodiversity Management in Tropical Agroforestry Landscapes
578 Be Optimized? *PLoS One*, 7, 1–7

579 Kissling, W.D. & Carl, G. (2008). Spatial autocorrelation and the selection of simultaneous
580 autoregressive models. *Glob. Ecol. Biogeogr.*, 17, 59–71

581 Kreft, H. & Jetz, W. (2007). Global patterns and determinants of vascular plant diversity.
582 *PNAS*, 204(14), 5925–5930

583 Liaw, A. & Wiener, M. (2002). The randomforest package. *R News*, 2, 18–22

584 Lindenmayer, D.B., Hulvey, K.B., Hobbs, R.J., Colyvan, M., Felton, A., Possingham, H., *et*
585 *al.* (2012). Avoiding bio-perversity from carbon sequestration solutions. *Conserv.*
586 *Lett.*, 5, 28–36

587 Locatelli, B., Imbach, P. & Wunder, S. (2013). Synergies and trade-offs between ecosystem
588 services in Costa Rica. *Environ. Conserv.*, 41, 27–36

589 Mantyka-Pringle, C.S., Visconti, P., Di Marco, M., Martin, T.G., Rondinini, C. & Rhodes,
590 J.R. (2015). Climate change modifies risk of global biodiversity loss due to land-

cover change. *Biol. Conserv.*, 187, 103–111

Midgley, G.F. & Bond, W.J. (2015) Future of African terrestrial biodiversity and ecosystems under anthropogenic climate change. *Nat. Clim. Chang.*, 5, 823–829

Midgley, G.F., Bond, W.J., Kapos, V., Ravilious, C., Scharlemann, J.P.W. & Woodward, F.I. (2010). Terrestrial carbon stocks and biodiversity: Key knowledge gaps and some policy implications. *Curr. Opin. Environ. Sustain.*, 2, 264–270

Montesino Pouzols, F., Toivonen, T., Di Minin, E., Kukkala, A.S., Kullberg, P., Kuusterä, J., et al. (2014) Global protected area expansion is compromised by projected land-use and parochialism. *Nature*, 516, 383–386

Murray, J.P., Grenyer, R., Wunder, S., Raes, N. & Jones, J.P.G. (2015). Spatial patterns of carbon, biodiversity, deforestation threat, and REDD+ projects in Indonesia. *Conserv. Biol.*, 29, 1434–1445

Newbold, T., Hudson, L.N., Arnell, A.P., Contu, S., Palma, A. De, Ferrier, S., et al. (2016). Has land use pushed terrestrial biodiversity beyond the planetary boundary? A global assessment. *Science*, 353, 288–291

Normand, S., Ricklefs, R.E., Skov, F., Bladt, J., Tackenberg, O. & Svenning, J.-C. (2011). Postglacial migration supplements climate in determining plant species ranges in Europe. *Proc. R. Soc. B*, 278, 3644–3653

Olson, D.M., Dinerstein, E., Wikramanayake, E.D., Burgess, N.D., Powell, G.V.N., Underwood, E.C., et al. (2001). Terrestrial Ecoregions of the World: A New Map of Life on Earth. *Bioscience*, 51, 933

Paoli, G.D., Wells, P.L., Meijaard, E., Struebig, M.J., Marshall, A.J., Obidzinski, K., et al. (2010). Biodiversity Conservation in the REDD. *Carbon Balance Manag.*, 5, 1-9

Putz, F.E. & Redford, K.H. (2009). Dangers of carbon-based conservation. *Glob. Environ. Chang.*, 19, 400–401

R Core Team. (2015). R: A language and environment for statistical computing. R Foundation for Statistical Computing. <http://www.R-project.org/>

Rahbek, C. (2005). The role of spatial scale and the perception of large-scale species-richness patterns. *Ecol. Lett.*, 8, 224–239.

Rondinini, C., Di Marco, M., Chiozza, F., Santulli, G., Baisero, D., Visconti, P., et al. (2011)

621 Global habitat suitability models of terrestrial mammals. *Philos. Trans. R. Soc. Lond.*
622 *B. Biol. Sci.*, 366, 2633–41

623 Rosenzweig, M.L. (1968). Net Primary Productivity of Terrestrial Communities : Prediction
624 from Climatological Data. *Am. Nat.*, 102, 67–74

625 Ruesch, a S. & Gibbs, H.K. (2008). *New IPCC Tier-1 Global Biomass Carbon Map for the*
626 *Year 2000. Carbon Dioxide Inf. Anal. Center, Oak Ridge Natl. Lab. Oak Ridge, USA.*
627 Available at: <http://cdiac.ornl.gov>. Last accessed

628 Saatchi, S.S., Harris, N.L., Brown, S., Lefsky, M., Mitchard, E.T.A., Salas, W., *et al.* (2011).
629 Benchmark map of forest carbon stocks in tropical regions across three continents.
630 *PNAS*, 108, 9899–9904

631 Santini, L., González-Suárez, M., Rondinini, C. & Di Marco, M. (2017). Shifting baseline in
632 macroecology? Unraveling the influence of human impact on mammalian body mass.
633 *Divers. Distrib.*, 23(6), 640–649

634 Scheffers, B.R., DeMeester, L., Bridge, T.C.L., Hoffmann, A. a., Pandolfi, J.M., Corlett, R.,
635 *et al.* (2016). The broad footprint of climate change from genes to biomes to people.
636 *Science*, 354(6313), aaf7671

637 Siikamäki, J. & Newbold, S.C. (2012). Potential biodiversity benefits from international
638 programs to reduce carbon emissions from deforestation. *Ambio*, 41, 78–89

639 Stevens, C.J., Dise, 1Nancy B., Mountford, J.O. & Gowing, D.J. (2004). Impact of Nitrogen
640 Deposition on the Species Richness of Grasslands. *Science*, 303, 1876–1880

641 Strassburg, B.B.N., Kelly, A., Balmford, A., Davies, R.G., Gibbs, H.K., Lovett, A., *et al.*
642 (2010). Global congruence of carbon storage and biodiversity in terrestrial
643 ecosystems. *Conserv. Lett.*, 3, 98–105

644 Strobl, C., Hothorn, T. & Zeileis, A. (2009). Party on. *R J.*, 1, 14–17

645 Sullivan, M.J., Talbot, J., Lewis, S.L., Phillips, O.L., Qie, L., Begne, S.K., *et al.* (2016).
646 Diversity and Carbon storage accross the tropical forest biome. *Sci. Rep.*, 6, 1–12

647 Thomas, C.D., Anderson, B.J., Moilanen, A., Eigenbrod, F., Heinemeyer, A., Quaife, T., *et*
648 *al.* (2013). Reconciling biodiversity and carbon conservation. *Ecol. Lett.*, 16, 39–47

649 Thomas, C.D., Cameron, A., Green, R.E., Bakkenes, M., Beaumont, L.J., Collingham, Y.C.,
650 *et al.* (2004). Extinction risk from climate change. *Nature*, 427, 145–148

- Tognelli, M.F. & Kelt, D.A. (2004). Analysis of determinants of mammalian species richness in South America using spatial autoregressive models. *Ecography*, 27, 427–436
- Trabucco, A. & Zomer, R.J. (2009). *Global Aridity Index (Global-Aridity) and Global Potential Evapo-Transpiration (Global-PET) Geospatial Data*. CGIAR Consort. *Spat. Inf.* Available at: <http://www.csi.cgiar.org>. Last accessed: 01 Dec 2016
- United Nations General Assembly. (2015). *Transforming our world: the 2030 Agenda for Sustainable Development*.
- USGS. (2006). *Shuttle Radar Topography Mission 3 arc second version 2.0*. Available at: www.landcover.org/data/srtm. Last accessed: 01 Dec 2016
- Venter, O. & Koh, L.P. (2012). Reducing emissions from deforestation and forest degradation (REDD+): Game changer or just another quick fix? *Ann. N. Y. Acad. Sci.*, 1249, 137–150
- Venter, O., Laurance, W.F., Iwamura, T., Wilson, K. a, Fuller, R. a & Possingham, H.P. (2009a). Harnessing carbon payments to protect biodiversity. *Science*, 326, 1368
- Venter, O., Meijaard, E., Possingham, H., Dennis, R., Sheil, D., Wich, S., *et al.* (2009b). Carbon payments as a safeguard for threatened tropical mammals. *Conserv. Lett.*, 2, 123–129
- Venter, O., Sanderson, E.W., Magrach, A., Allan, J.R., Beher, J., Jones, K.R., *et al.* (2016). Sixteen years of change in the global terrestrial human footprint and implications for biodiversity conservation. *Nat. Commun.*, 7, 1–11
- Visconti, P., Bakkenes, M., Baisero, D., Brooks, T., Butchart, S.H.M., Joppa, L., *et al.* (2016). Projecting global biodiversity indicators under future development scenarios. *Conserv. Lett.*, 9, 5–13
- Watson, J.E.M., Dudley, N., Segan, D.B. & Hockings, M. (2014). The performance and potential of protected areas. *Nature*, 515, 67–73
- Watson, J.E.M., Jones, K.R., Fuller, R.A., Di Marco, M., Segan, D.B., Butchart, S.H.M., *et al.* (2016). Persistent Disparities between Recent Rates of Habitat Conversion and Protection and Implications for Future Global Conservation Targets, 0, 1–9

List of Figures

Fig. 1 Carbon and biodiversity maps used in the analyses. Panel (a) reports the above-ground carbon density in tropical and subtropical areas. Panel (b) reports the number of amphibian, bird and mammal species occurring in each grid cell.

Fig. 2 Correlation between species richness and carbon storage measured at different biogeographical extents. The plots represent the mean and 95% standard credible interval of the Spearman's correlation coefficient among all biogeographical units in a given spatial extent. Panel (a) is based on total species richness, panels (b-d) are based on the richness measured for individual groups.

Fig. 3 Correlation between vertebrate species richness carbon in tropical and subtropical ecoregions. The map reports the Spearman's correlation coefficient between species richness and carbon density observed in 10 km grid cells within each ecoregion. Ecoregions with shaded colours are characterised by low standard deviation in species richness and carbon density (lowest quartile of observed SD among ecoregions). Areas in light grey were excluded from analyses as they lack carbon data (see Methods for a description of the input variables).

Fig. 4 Frequency distribution of the percentage of the variance explained by SAR models relating species richness and carbon density to environmental variables in each ecoregion. Panels (a) and (b) reports the variance explained by species richness models, while panels (c) and (d) reports the variance explained by carbon density models. Panels (a) and (c) reports the total variance explained, while panels (b) and (d) only reports the variance explained by the model variables, after excluding the portion of variance explained by spatial autocorrelation.

Fig. 5 Variable importance plot of the Random Forest regression model for the prediction of biodiversity-carbon correlation across ecoregions. The variables are ranked on the basis of

their importance for the reduction of Mean Square Error and Node Impurity during the random forest classification routine.

Variable description: 'carb.R2nsp' non-spatial R^2 of the carbon prediction model; 'biodiv.R2nsp' non-spatial R^2 of the species richness prediction model; 'biodiv.sd' standard deviation of species richness; 'impact_avgyear' average year of first human land use in the ecoregion; 'carb.sd' standard deviation of carbon density; 'REALM' biogeographical realm; 'highHFP' proportion of the ecoregional area overlapping with human footprint values >3 ; 'BIOME' biogeographical biome; 'avg_fire', average fire extent; 'tot_area' total land area; 'fractal' fractal dimension.

Fig. 6 Bivariate partial plot relating the observed correlation between species and carbon density to the performance of species richness (biodiv.R2nsp) and carbon (carb.R2nsp) environmental prediction models.

ele_12903_f1.tiff

ele_12903_f2.tiff

ele_12903_f3.tiff

ele_12903_f4.tiff

ele_12903_f5.tiff

ele_12903_f6.tiff

Minerva Access is the Institutional Repository of The University of Melbourne

Author/s:

Di Marco, M;Watson, JEM;Currie, DJ;Possingham, HP;Venter, O

Title:

The extent and predictability of the biodiversity-carbon correlation.

Date:

2018-03

Citation:

Di Marco, M., Watson, J. E. M., Currie, D. J., Possingham, H. P. & Venter, O. (2018).
The extent and predictability of the biodiversity-carbon correlation.. *Ecol Lett*, 21 (3),
pp.365-375. <https://doi.org/10.1111/ele.12903>.

Persistent Link:

<http://hdl.handle.net/11343/284611>